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Presenting a Multi-objective Optimization Model for Resource-Constrained Project Scheduling Regarding Financial Costs, Time Delays and the Reliability Function

Saeideh Naderi[1], Mohsen Vaez-Ghasemi[2,*], Farzad Movahedi Sobhani[3]

[1] Department of Industrial Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran; saedeh_na@yahoo.com.
[2] Department of Mathematics, Rasht Branch, Islamic Azad University, Rasht, Iran; mohsen.vaez@gmail.com.
[3] Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran; f-movahedi@srbiau.ac.ir.

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Abstract

The common presuppositions and limitations regarding the Resource Constrained Project Scheduling Problem (RCPSP) were investigated in addition to their reliability in modeling in order to investigate the possibility of availability of renewable resources using a new attitude. The objective of modeling RCPSP was the quantification of total costs and minimization of delays in projects. Hence, in order to mathematically model RCPSP, the first non-linear complex integer math programming was transformed into a linear programming model using the features of exponential functions. To solve the final linear math problem, some experimental examples were designed in different dimensions aiming to study the performance and efficiency of the designed model. For solving low-dimension problems, the exact (epsilon) constraint multi-objective optimization method was used in the Lingo software. A meta-heuristic algorithm called NSGA-II was employed to find solutions for high-dimension problems that the Exact method could not solve. The results of using these algorithms and the statistical analysis (with 95% reliability) indicated that the performance was suitable for the Genetic Algorithm (GA). The calculation error between the Exact method and the meta-heuristic method for the three target categories of total cost, time delay, and reliability was calculated based on the obtained results. The number of errors in calculating the total cost was 26%, 19%, and 5%, respectively. Also, the delay objective function error was equal to 28%, 24%, 12 %, and 14%, respectively. Finally, the reliability objective function error value was equal to 8%, 3%, 29%, and 36%, respectively. Accordingly, it can be concluded that this meta-heuristic algorithm (GA) has more efficiency and more apposite performance for the recommended model compared with the Exact optimization software. The use of the math model designed in this study can result in decreasing the time delays in projects and the costs of scheduling problems, as well as increasing the reliability in multi-mode activities.

Keywords: Project scheduling, Restrained resources, Time delays, Reliability, Multi-mode activities.

1 | Introduction

Resource Constrained Project Scheduling Problem (RCPSP) has taken a central place in project management and generated a rich body of research since its introduction by Pritsker et al. [1] in 1969. This problem is

Corresponding Author: mohsen.vaez@gmail.com
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important for employees and has various applications, from project management software to production planning and scheduling systems [2]. RCPSP is one of the most applied issues, and its subsets involve all other scheduling problems [3]. It incorporates activities that should be scheduled regarding the constraints in resources and prerequisite relations in order to reduce time delays to the minimum. RCPSP has become standard and famous in project scheduling. Many researchers have become interested in RCPSP and rendering initiatives and exact scheduling solutions for it. RCPSP is looking for a suitable sequence of performing activities so that the prioritizing constraints of a project system and various types of resource constraints are evaluated simultaneously, and definite measurement criteria, including project performance period, cost, and number of delaying activities, are optimized. This type of problem is salient in science and application [4].

In practice, a resource often represents a group of workers with the same specialized skills or a group of identical machines. Hence, the assumption that resource requests and availability are integrated is satisfied. RCPSP involves finding a schedule of activities, i.e., a set of start times, with minimum project duration (project duration). Project length is defined as the time difference between the start and finish of the project, with the constraints that each activity is completed exactly once, each activity starts if all its predecessors are completed, and for each period and each resource type, the kth amount of renewable resources required by the ongoing activities does not exceed the available resources.

Over the past 40 years, several families of discoveries have been proposed for RCPSP, which can be broadly classified into three main classes: a) single-pass heuristics, b) multi-pass heuristics (mostly developed by 1990), and c) meta-heuristics, whose growth has occurred in the past two decades. In early single-pass and multi-pass heuristics, more emphasis is placed on quickly achieving a feasible schedule. These two classes of heuristics use a schedule generation scheme, serial or parallel, and one or more priority rules to construct one or more schedules. Meta-heuristics follow rules to explore the deepest regions of the solution space in the hope of finding high-quality solutions but at the cost of increasing computation time over exploration. Meta-initiative has proven to be very powerful for solving RCPSP. Simulated annealing, Tabu search, artificial immunity, bee colony optimization, Genetic Algorithm (GA), particle swarm optimization, sparse search, and ant colony optimization are frequently listed in recent reviews [2].

In this paper, we focus on multi-objective meta-heuristic and deterministic optimization models to solve RCPSP. For this purpose, we first provide a mathematical modeling for RCPSP. Then, we solve it using the deterministic algorithm and show its applicability using the meta-heuristic algorithm. To do this, in the model of RCPSP presented in the current study, in addition to previous presuppositions and constraints, reliability is considered a novel applicable objective function. This means that the maximum availability of renewable resources is achieved by maximizing reliability, and consequently, the corresponding constraints are added to the model. The model is considered a multi-objective function of costs, time delays, and reliability. It is worth noting that multiple modes were considered for activities in this project, a rare case in other criteria of project scheduling.

The objective function relative to reliability resulted in the model becoming non-linear. At the end, a linear one is presented. Since the optimization of RCPSP has its complications, in this study, the meta-heuristic GA is used to solve the math model, and the final optimized answers are compared with those of the Exact (Epsilon) method. In the next section, the problem and its constraints, variables, and parameters are modeled. Afterward, numeric examples are presented and solved by the Lingo program and the NSGA-II meta-heuristic algorithm, which is very useful for solving multi-objective optimization problems. The final results of the two methods are compared. In the end, conclusions and suggestions are rendered for future studies. Therefore, two main contributions of the current research are as follows:

I. Presenting an optimization model to solve RCPSP using mathematical modeling and NSGA-II meta-heuristic algorithm.

II. Considering the maximum reliability as the objective function of RCPSP in order to maximize the availability of renewable resources.

Accordingly, the purpose of this article is threefold: 1) identifying the basic elements for the mathematical modeling of RCPSP, 2) solving the model using the deterministic method, and 3) showing the applicability of the mathematical model using the meta-heuristic algorithm.

The rest of the paper has been organized as follows: Section 2 presents the literature review. Section 3 deals with research methodology, problem statement, and research modeling. Section 4 involves the main research findings. Section 5 deals with discussions and identified managerial insights. Finally, Section 6 presents conclusions and suggestions for future studies.

2|Literature Review

Hartmann and Briskorn [5] developed a model regarding the different types of RCPSPs. They presented a comprehensive outlook of RCPSPs categorized based on their structure. They summarized the generalizations of activity natures, prerequisite relationships, and resource constraints. Moreover, they discussed replacement objectives and scheduling approaches for multiple projects. In the end, they presented multiple methods, maximum and minimum time delays. and goals based on net present value. Coelho and Vanhoucke [6] studied Multi-mode RCPSP (MRCPSP) using SAT and RCPSP solutions. They presented a new approach to solve MRCPSPs in which a unique activity is selected among the available sets in order to make a possible scheduling project problem having one resource and a prerequisite relation with the least time delay. This type of problem is known as an "NP-hard problem" that is solved by various exact and meta-heuristic (heuristic) approaches. The new algorithm presented in this study transforms the problem into a multi-mode one and can render similar or better results compared to other methods proposed in the literature. Wang and Fang [7] presented an effective estimation and usage of distribution algorithms for MRCPSPs.

In the estimation of distribution algorithms, units are encoded based on an activity-based list and decoded using a multi-mode series of scheduling production plans. As a result, a new probability model is designed, and an updating mechanism is presented for sampling. For having a better quality in searching, a multi-mode repetition, which moves forward and backward, is used along with a local search method. The results of simulating based on comparison with other algorithms show that the approach is efficient.

Khemakhem and Chtourou [8] studied effective Robust Measures (RMs) for RCPSP. They analyzed the most salient criteria and presented numerous new RMs. The effectiveness of RMs was evaluated in a certain criterion via a five-stage approach using possible correlations among the measures as well as a pre-defined application measure. The relations and effectiveness of some new measures were also studied. It was confirmed that the presented measures were statistically more effective compared to those in previous literature. Therefore, these measures can help project managers choose the most robust scheduling, make distinctions, and score time-delay solutions. Naber and Kolisch [9] presented complex integer number scheduling models for RCPSPs using flexible resource profiles, as well as primary, dependent, and independent resources. Four complex integer math models were used with discrete time. The analysis results revealed that the compact-based variable performs considerably better than the other models in terms of answer quality and calculation time. In their problem, the start time, the resource profile, and the time necessary for each activity were determined in order to minimize the time delays of prerequisite relations, the limited availability of multiple resources, and resource profile constraints. The preprocessing and heuristic methods based on priority were used to calculate the lower and upper bounds of time delays.

Bettemir and Sonmez [10] employed a multi-heuristic compound GA in which refrigeration is simulated for solving RCPSP. This strategy was used to integrate the ability of parallel searching in GA, which can balance the refrigeration simulation in order to achieve the best results. Their approach was tested using the experimental problems of benchmarking, and the best answers of the algorithm were achieved. In their calculation tests, an absolute GA and seven heuristic ones were used in project scheduling software. The results indicated that the strategy increased the convergence of GA and is a suitable replacement for RCPSP. Zheng and Wang [11] presented a multi-factor optimization algorithm for RCPSPs, where numerous factors work in a grouped environment, and each factor renders a possible answer. These factors are evaluated using

four important elements: social behavior, automatic behavior, self-learning, and adjusting environments. Some factors immigrate to improve the environment and share information dynamically. Implementing a multiple-factor approach is done to solve the problem, and the impact of key parameters is analyzed based on the Taguchi experiment design. The results are achieved by using three sets of benchmarking samples, which shows the effectiveness of the multiple-factor model in solving RCPSP. Chakrabortty et al. [12] analyzed MRCPSP at the time of disorders of resources. They presented two discrete-time models to analyze two different disorder-of-resource scenarios. For this purpose, an active rescheduling approach was recommended for unique sets of disorders when there is no information regarding them. In order to evaluate the approaches, a set of numeric multi-mode and ten, twenty, and thirty activity samples were used after introducing the produced random disorder events. Experimental studies were also done to identify the various factors that contribute to the process of fixing disorders.

Lamas and Demeulemeester [13] used an active scheduling approach to solve RCPSP, considering the project's activity period as uncertain. Their objective was to develop a new method for active basic scheduling. The most important advantage of this method was acting completely independent of politics. Unlike the traditional approaches, in this method, a RM is determined, and a branch and bound method is introduced for approximating the mean of samples from the main problem. The calculation findings indicated that this method is more effective than previous ones in various RMs. Elsayed et al. [14] presented an RCPSP using a shared optimization algorithm. They presented a general framework for solving the problem by employing various heuristic approaches. Each approach had numerous search operators, which were used in a self-adjusting way. The most emphasis was on the better performance of algorithms and their search operators. In order to improve convergence and present better answers, a local search approach was introduced in the primary population. The presented method renders the best answers for problems with 30 and 60 activities and is competitive in the case of projects with 120 activities.

Leyman and Vanhoucke [15] analyzed RCPSPs and cash capitals and flows with discounts for optimization of the net present value. The problems in this study included capital constraints that force the project to have a positive balance. Therefore, it is important to schedule activities in such a sequence so that capital is available. Also, two new schedulings were presented to improve the feasibility of the capital. In the end, the approach was tested on a big data set, and the value added was validated. Rostami et al. [16] presented new strategies for RCPSPs where the project activities had random times. In the new class of policies, there is a policy for analyzing prioritization in the preprocessing phase. The rest of the scheduling decisions are online. A two-phase local search algorithm was used to optimize answers in this class. The results indicated that the algorithm moves towards fruitful answers effectively and performs better than other existing algorithms.

Chen et al. [17] introduced effective priority principles in RCPSP. They analyzed the performance of 17 heuristic algorithms in the priority principle and also the technique of correction on scheduling projects. Among the 17 priority principles, 12 policies were selected from the literature in which certain RCPSPs were used. The other five policies were recently designed based on uncertain data. They analyzed the effectiveness of 17 priority principles on benchmarking data and tested the project features. The results of problems with high dimensions showed that the best priority principle is not necessarily the best solution to solve uncertain problems.

Birjandi and Mousavi [18] studied RCPSP in a fuzzy way in numerous ways. They used a heuristic approach to solve it. To model the problem, they presented a fuzzy complex integer number non-linear model under uncertain conditions. Accordingly, a compound heuristic approach was used to minimize the cost of the completion of the project. In order to render the primary high-quality answers, a heuristic approach was designed based on the distribution principles. Afterward, in order to select an appropriate method for flexible activities, a meta-heuristic approach was presented based on the optimization of zero and one particle. Finally, a GA was used to achieve the best answers.

Servranckx and Vanhoucke [19] employed a forbidden search method for RCPSP, which had replacement subgraphs. In this scheduling problem, there are available replacement methods belonging to work packages

in which the desired activities must be scheduled alternatively in the structure of the project. Therefore, the presented problem has two subproblems: choice and scheduling. The salient characteristic of this study is categorizing the different types of replacement subgraphs in a comprehensive categorizing matrix based on dependencies among the replacements in the project's structure. They investigated the overall performance of the meta-heuristic approach and various improvement strategies using the set of developed data. Moreover, they indicated the impacts of various parameters on the equality of the answers and analyzed the effect of discrete features of the resource on the selection process. Chakraborty et al. [20] investigated MRCPSPs using the nearest neighbor's method, which is a heuristic approach. They were trying to find a fast and close-to-optimization solution for MRCPSPs in which the projects had the necessities of renewable and nonrenewable resources. The presented a complicated, uncertain problem with multi-dimensions, which was solved via the exact heuristic and meta-heuristic methods. In addition, they presented a heuristic approach to searching for the nearest neighbor of a corrected variable. In an experimental study, a standard set including 3239 samples was considered, and the results showed that their findings can be used as a benchmark for similar future studies.

Araujo et al. [21] investigated the strong bounds for RCPSP using cut and preprocessing programs. They used a cut algorithm to separate five different families of cut problems. Also, they applied a new preprocessing method to strengthen resource-based constraints. The new versions of famous prerequisites and covering problems were used in all repetitions of a dense contradictory graph, considering the feasibility and optimization conditions of separating the planes. The strategies could improve the linear releasing bounds and optimization and, thereby, made it possible for a complex integer linear programming problem solver to achieve optimized answers for 754 different samples. The main linear programming formulization was not usable in this case.

Zamman et al. [22] presented an evolutionary approach for RCPSPs in which changes in the project were considered uncertain. They considered the time of activity as an integer number or the actual value or both in an uncertain form. In order to solve the uncertain optimization problem, they used a simulating evolutionary approach, including two multiple and two heuristic operators to perform its process. Then, numerous samples were evaluated based on uncertain times. In this approach, presenting the answer is different from the necessary amount in the math programming approach, which does not need separation of periods. Balouka and Cohen [23] used a robust optimization approach in order to solve RCPSPs. Their objective was to quantify the project period in the worst-case scenario when deciding on activity modes, resource specification, and basic scheduling. Benders' decomposition approach solved their problems. They considered a multi-dimensional uncertain set in which the level of prudence can be corrected.

Mahmud et al. [24] proposed a customized evolutionary algorithm integrated with three heuristics for singular activities. The first heuristic was based on the earliest start time with the aim of rectifying an infeasible schedule. The second heuristic was based on neighborhood swapping, which was used to find the best possible alternatives. The third heuristic was used to enhance the quality of the schedule further. The performance of the proposed framework was tested by solving a wide range of benchmark problems, and the results revealed that the proposed approach outperformed the existing algorithms. In addition, statistical and parametric test results showed the value and characteristics of the proposed approach. Liu et al. [25] conducted a study regarding the decomposition of search areas for RCPSPs. They confirmed the theoretical equivalent for the search areas before and after the decomposition process. The results indicated that this approach can be easily used in reverse algorithms. Four decomposition-based approaches were categorized into three classic algorithms in order to improve the quality of scheduling under certain conditions. Also, the most apposite decomposition strategy was evaluated for each algorithm.

Gehring et al. [26] investigated the integration of material flows in RCPSPs. They developed their problem with regard to relative constraints to released materials when the project is being implemented. These constraints are the results of the limited processing capacities for materials and the maximum of facilities for

storage. The scheduling problems of production with convergent material flows were studied in detail. They modeled the flow of materials using modelization operations.

Issa et al. [27] presented RCPSP modeling under different activity assumptions. For this purpose, they introduced the interruptible and flexible planning project activity concept and developed a heuristic method to accomplish the reassessment of category types from A to B and D. First; the heuristic algorithm changes the Interruptible Activities (IAs) under categories A, B and D. Then Critical Interruptible Activities (CIAs) that have significant impacts in reducing the project makespan are identified. This increases the manager's decision choices with respect to scheduling activities as category type A, B, or D. The methodology facilitates an understanding of how A, B, and D interpretability assumptions affect the project makespan and helps the project manager to selectively choose how specific activities in a project should be managed. Goncharov [28] presented an improved GA for RCPSP. For this purpose, the schedules are constructed using a heuristic algorithm that builds active schedules based on priorities, taking into account the degree of criticality for the resources. The degree of the resource's criticality is derived from the solution of a relaxed problem with a constraint on accumulative resources. Some instances of studies performed based on this criterion are as follows [29–31]. It is worth noting that problems with resource constraints have been studied in many cases. In the problems of scheduling projects, a set of activities is studied considering their ordering and constraints on the availability of renewable and nonrenewable resources. In the model analyzed in the current study, different modes of performing activities have also been considered.

Accordingly, the main advantage of this article compared to previous studies is that multi-objective optimization models have been used both meta-heuristically and deterministically to solve RCPSP. To do this, mathematical modeling for RCPSP is first presented, and then the problem is solved using a deterministic algorithm. Finally, we show its application using the meta-heuristic algorithm. The use of mathematical modeling and deterministic solutions provides the possibility for managers to solve RCPSPs in small dimensions easily and quickly, as well as problems in large dimensions by using meta-heuristic algorithms. Thus, the presented framework will be compatible with all conditions. For this purpose, in the presented RCPSP model, in addition to the assumptions and limitations that previous studies have considered, the reliability objective function has been added as a new and applicable objective to RCPSP. The addition of this objective function means that the availability of renewable resources is taken into account by maximizing reliability. Hence, the related constraints are added to the model.

2.1 | Problem Statement

First, the categories (sets), variables, and parameters are defined in order to present the basic model in RCPSP. We intended to investigate RCPSP over many periods, including numerous activities and different modes. In addition, the resources are categorized into renewable and nonrenewable resources. One of the decisions made after solving the math model is starting or not starting an activity in a certain mode. Another example of decisions is the necessity of a renewable resource in a certain amount at the start of the project. In this problem, the time of project activities is also determined. Finally, after determining the decisions regarding the problem, the minimum time delays in the project are calculated in an optimized mode. Notably, the objectives of this problem include minimizing the time delays and costs of scheduling and maximizing the reliability and availability of resources. In the end, the final decisions will be optimized.

2.2 | Problem Modeling

In this section, all indices, parameters, variables, constraints, and objective functions are defined.

Indices

I	The category of activities.
M	The category of the modes for each activity.

K	The category of renewable resources.
L	The category of nonrenewable resources.
T	The category of periods.

Parameters

TC	Total cost.
MS	Delays.
R	Reliability.
T	Time.
α_{im}	The minimum time for performing activity i in the mode m.
β_{im}	The maximum time for performing activity i in the mode m.
F_{im}	Activity i start time in mode m.
S_{im}	Activity end time in mode m.
$N^r_{k,t}$	Number of Kth renewable resources in t th day.
$r^r_{i,m,k}$	Necessary units from Kth renewable resource ($K \in R$).
a^r_k	Number of Kth renewable resources.
$r^n_{i,m,l}$	Necessary units from Lth nonrenewable resource ($K \in R^n$).
a^n_l	The number of Lth nonrenewable resources.
$R^r_{k,t}$	Reliability (availability) of the Kth renewable resource as necessary in the tth day.
p^r_k	Availability of the Kth renewable resource.
u^r_k	The upper limit of the Kth renewable resource.
l^r_k	The lower limit of the Kth renewable resource.
c^r_k	The cost of each renewable resource unit.
c^n_k	The cost of each nonrenewable resource in all days and all available consuming resource.

Variables

$X_{(i,m,t)} = \begin{cases}1\\0\end{cases}$	If the activity i is in mode m and starts in time t.
$Y^r_{k,a',t,N'} = \begin{cases}1\\0\end{cases}$	If the kth renewable resource is needed as much as N' in the tth day, when generally the amount of a' of it, is available since the start of the project:
$d_{i,m}$	The period of doing activity i in mode m.

Objective functions

Subsequently, the model of this study was analyzed considering the functions of the minimum of the total cost and time delays and maximizing reliability with the aim of availability of renewable resources. Also, the subsequent constraints are added to it and explained:

$$\text{Min} \sum_{t=1}^{T}\sum_{k\in R^2} C_k^r . a_k^r + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{m=1}^{M_i}\sum_{l\in R^n} C_l^n r_{i,m,l}^n x_{i,m,t.} \quad (1)$$

The first objective function indicates the quantification of the project costs resulting from the total of renewable and nonrenewable resources.

$$\text{Min} \sum_{t=es_{n+1}}^{ls_{n+1}} tx_{n+1,1,t}. \quad (2)$$

The second objective function indicates the quantification of the time delays resulting from the sum of the products of each time delay in variable 0 and relative activity.

$$\text{Max} \prod_{t=1}^{T}\prod_{k\in R^2} R_{k,t}^r. \quad (3)$$

The third objective function indicates the maximization of the reliability of the whole project from which, for example, the reliability of a renewable resource is achieved via its availability in times 1,…., T.

Constraints

$$\sum_{m=1}^{M_i}\sum_{t=es_1}^{ls_i}\left(t+d_{i,m}\right)x_{i,m,t} \le \sum_{m=1}^{M_i}\sum_{t=es_1}^{ls_i} tx_{j,m,t}, \quad \text{for all } (i,j) \in N. \quad (4)$$

Constraint (4) is the sequence of activity performances regarding prerequisite constraints when lag=0.

$$\sum_{m=1}^{M_i}\sum_{t=es_1}^{ls_i} x_{i,m,t} = 1, \quad \text{for all } i \in N. \quad (5)$$

Constraint (5) guarantees that each activity is done in one mode, one time, and using the relative resources in that same mode.

$$\sum_{i=1}^{n}\sum_{m=1}^{M_i} r_{i,m,k}^r \sum_{s=\max\left(t-d_{i,m},es_1\right)}^{\min(t-l,ls_i)} x_{i,m,s} \le a_k^r, \quad \text{for all } k \in R^r \text{and } t = l,\dots,T. \quad (6)$$

Constraint (6) states that the number of kth renewable resources in the tth day is less than the total one of the same resource.

$$\sum_{i=1}^{n}\sum_{m=1}^{M_i} r_{i,m,k}^r \sum_{t=es_1}^{ls_i} x_{i,m,t} \le a_l^n, \quad \text{for all } l \in R^n. \quad (7)$$

Constraint (7) is a natural one regarding the availability of nonrenewable resources and is indicative of the number of Lth renewable resources.

$$L_k^r \le a_k^r \le U_k^r, \quad \text{for all } k \in R^r. \quad (8)$$

Constraint (8) is a natural one of the kth renewable resources, which is limited between an upper and lower limit.

$$R^r_{k,l} = \sum_{g=N^r_{kj}}^{a^r_k} \binom{a^r_k}{g}.(p^r_k)^g.(1-p^r_k)^{a^r_k-g}, \quad \text{for all } k \in R^r \text{and } t = 1, \ldots, T. \tag{9}$$

Constraint (9) is regarding the project's reliability; it states the availability and choice of renewable resources among the existing ones using a binomial distribution.

$$\alpha_{im} \le d_{im} \le \beta_{im}, \quad \text{for all } i, m. \tag{10}$$

Constraint (10) guarantees that the minimum and maximum time of performance exists for performing activity i in the mode m.

$$F_{im} - S_{im} = d_{im}x_{imt}, \quad \text{for all } i, m, t. \tag{11}$$

Constraint (11) shows that the length of performing activity I in the mode m must be equal to the time difference between start and end times.

$$x_{im,t+1} \le x_{imt}, \quad \text{for all } i, m, t. \tag{12}$$

Constraint (12) shows that in a possible answer, the next section is scheduling if and only if the previous activity is scheduled.

$$x_{i,m,t}, Y^r_{k,a',t,N'} \in \{0,1\}, \quad \text{for all } i \in N, m = 1, \ldots, M_i, t = 1, \ldots . T, \text{for all } k, a. \tag{13}$$

Constraint (13) determines variables 0 and 1 for kth renewable resources.

$$d_{i,m}m \ge 0, \quad \text{for all } i, m. \tag{14}$$

Constraint (14) is a noon-negative variable stating the time length of performing an activity.

The presented multi-objective model is non-linear because of *Constraint (9)* and the objective *Function (3)*. In order to make it linear, the features of an exponential function were used, and the variable $\gamma^r_{k,a',t,N'}$ is added according to the definition mentioned when introducing variables.

$$L_n(R_{total}) = L_n\left(\prod_{l=1}^{T} \prod_{k \in R^r} R^r_{k\ ,t}\right) = \sum_{t=1}^{T} \sum_{k \in R^r} (R^r_{k\ ,t}). \tag{15}$$

$$\gamma^r_{k,a',t,N'} = L_n(R^r_{k\ ,t}) \text{ if } a^r_k = a' \text{and } N^r_{k\ ,t} = N',$$

$$\gamma^r_{k,a',t,N'} = \ln\left(\sum_{g=N'}^{a'} \binom{a'}{g}.(p^r_k)^g.(1-p^r_k)^{a'-g}\right) \text{for all } k \in R^r \text{and } t = 1, \ldots, T, a' = L^r_k, \ldots, U^r_k \text{ and } N' = 0, \ldots, a'. \tag{16}$$

Therefore, the resulting *Statement (17)* replaces the objective *Function (3)*, and the final *Statement (18)* replaces *Constraint (9)*.

$$\text{Max } L_n(R_{total}) = \sum_{t=1}^{r} \sum_{k \in R^r} \sum_{a'=L^r_k}^{U^r_k} \gamma^r_{k,a',t,N'} \cdot y^r_{k,a',t,N'}. \tag{17}$$

$$\sum_{a'=L^r_k}^{U^r_k} \sum_{N'=0}^{a'} y^r_{k,a',t,N'} = 1, \quad \text{for all } k \in R^r \text{and } t = 1, \ldots, T. \tag{18}$$

2.2.1 | Solution method

Since the model presented in this study possesses many objective functions, multi-objective optimization methods were used to solve it. The Epsilon constraint approach solves low-dimension problems, and average- and high-dimension problems are solved with the NSGA-II meta-heuristic algorithm as a multi-objective optimization method [32].

The epsilon constraint method

Epsilon constraint is one of the most popular methods used in multi-objective optimization, and it will also be used in this study as recommended by [33–35]. In this method, one of the objective functions is used for optimization, and other functions are transformed into constraints with a limit above ε.

The primary idea of this method is that, first, one of the multiple objectives is set as the main objective function of optimization, and the other functions are transferred to the constraints of the problem considering upper and lower limits for each function.

By changing the right limit of the functions' constraints in their upper limits towards their lower limits and repetition of the solution, all possible Pareto answers will be achieved for multi-objective problems.

The general shape of an epsilon constraint method is as follows:

$$\begin{aligned} &\text{Min } Z_j(x), \\ &\text{s.t.} \\ &Z_k(x) + s_k = \varepsilon_k, \text{ for all } k \neq j, \\ &x \in X, s_k \in R^r. \end{aligned} \tag{19}$$

The sk is the covariate variable, which is related to the kth objective function.

2.2.2 | The meta heuristic algorithm non-dominated sorting genetic algorithm II (NSGA-II)

Multi-objective evolutionary algorithms using non-dominated sorting and intersecting are basically criticized because of three problems: 1) the complexity of calculations, 2) the non-elite approach, and 3) the necessity of determining an intersection parameter. In this section, an evolutionary GA, which is a non-dominated multi-objective and based on intersection (NSGA-II), is studied. This algorithm is able to solve all the above-mentioned problems. GA is a heuristic algorithm that uses the modelization of animal populations. In this algorithm, animals are similized into the amounts resulting from the objective functions and improvement in the features of the previous generation. The birth of a new generation out of the mating of previous generations assists in improving the objective functions. NSGA-II is one of the multi-objective modes of GA whose general procedure is as follows:

I. Generating a primary population.

II. Calculating the goodness of fit criteria.

III. Sorting the population based on the domination conditions.

IV. Calculation of crowding distance.

V. Selection based on population rank and calculation of distance: populations are selected in lower ranks. If p and q are two members of one rank, the member that has more crowding distance will be selected. Accordingly, the selection priority is first based on the rank and then the crowding distance.

VI. Intersecting and mutating to bear new children.

VII. Merging the primary and resulting population via intersecting and mutating.

VIII. Replacing the parents' population with the best members of the merged population in previous stages. First, the members of the lower ranks replace the previous parents. Then, they are sorted based on the crowding distance.

All the above-mentioned stages are repeated until optimization is achieved. The general procedure in NSGA-II is demonstrated in *Fig. 1*.

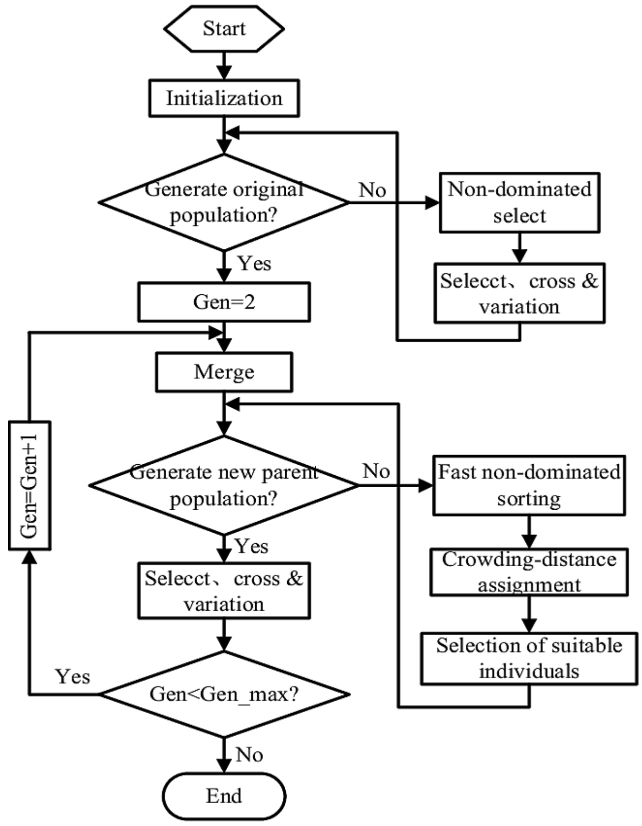

Fig. 1. The general performance of NSGA in flowchart.

GA is considered one of the first and most successful evolutionary algorithms, and its successful applications have been reported in various sciences. The most important strength of GA is that it is parallel and has several starting points for solving the problem so that it can search the problem space from several different directions in one moment. This problem increases the efficiency of GA in solving non-linear problems with a large space. In linear problems, each element is independent, and any change has a direct impact on a single part of the system, while in non-linear problems, a change in one part may have an uncoordinated effect on the whole system or a change in several elements may have a large effect on the system.

The parallelism of GA solves this type of problem. Another advantage of GA is that it is a blind watchmaker; in other words, it does not know about the problems it solves. When solving problems, GA shows random changes in the candidate solutions and uses the fit function to measure whether the changes have made progress or not. This action allows the algorithm to start solving the problem in a wider space. Since its decisions are essentially random, all possible solutions to the problem are open. Its other merits include good global searching, easy implementation, ability to optimize with discrete and continuous variables, and solving non-linear combined optimization problems under non-linear constraints of equality and inequality type.

The fast, non-dominated sorting approach

In a simple approach, to determine the answers of the first non-dominated front in a population whose number is N, each answer can be compared with many other answers in the population in order to discover whether it is non-dominated or not. This approach needs O (MN) number of comparisons in which M is the number of objectives. When this process continues until all members of the first level in the population are found, the total complexity is equal to O (MN2). In this stage, all individuals in the first non-dominated front are discovered. In order to find the individuals in the next non-dominated front, the answers of the first front are reduced temporarily. In the worst-case scenario, finding individuals on the second front needs an O (MN2) number of comparisons, especially when O(N) is the number of answers at the second and highest non-

dominated levels. Therefore, in the worst cases, there exists an N number of fronts and only one answer for each front, which needs an O(MN3) number of comparisons.

Firstly, two parameters are calculated for each answer: 1) number of dominations (np), i.e., number of answers dominating p, and 2) set of answers, Sp, dominated by answer p. This needs O (MN2) number of comparisons. The number of domination is zero for all answers in the first non-dominated front. For each answer of P equal to np=0, each member q of the set Sp is observed, and their number of domination is reduced to 1. As a result, if for each member q, domination is zero, they are put inside the set Q. These members belong to the second non-dominated front. Then, the above-mentioned procedure continues for each member of the set Q, and the third front is determined. This approach continues until all fronts are determined.

The estimation of density

In order to find out the density of answers around a certain answer in the population, the distance between the mean of two points around the two sides of that point in the objective function is calculated (see *Fig. 2*). Population distance is determined by using the closest neighbors to the points. The population distance of the ith answer in the front is equal to the mean of the cube length.

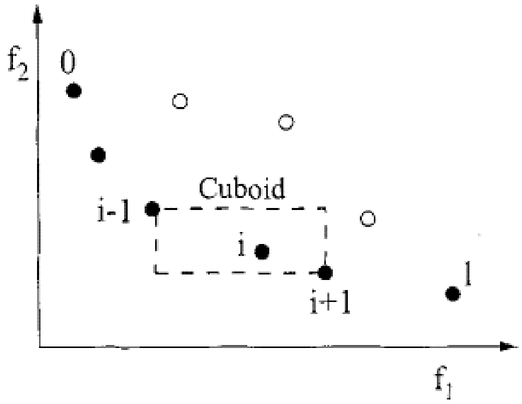

Fig. 2. The population distance.

The calculation of population distance necessitates that the population be sorted based on each objective function. For each function, the boundary values will be specified with a range of unlimited distances. All other median answers will be determined in the number of functions that have two compatible answers with a distance range equal to the absolute value of the normalized difference. The total population distance will be based on the total distances relative to each goal. Each objective function will be normalized before the population distance is calculated.

The population comparison operator

This operator guides the selection procedure to an optimized Pareto front in various stages of the algorithm. Let's suppose that each individual (i) has two features in the population:

I. Non-dominated rank.

II. Crowding distance.

Now, a relative order of the population comparison operator is determined:

$$\begin{aligned} &i \prec_n j \quad \text{if } (i_{rank} < j_{rank}), \\ &\quad \text{or } ((i_{rank} < j_{rank}), \\ &\text{and } (i_{distance} > j_{distance})). \end{aligned} \tag{20}$$

Between the two different answers with non-dominated ranks, the answers with lower ranks will be preferred. Otherwise, if the two answers belong to a single front, the selected answer will belong to the less crowded population.

The main ring

First, a random parent population is selected (P0) and sorted according to non-domination criteria. Each answer is specified to a rank equal to the non-domination level. The operators used for creating the children population Q0 whose number is N, are mutation, combinations which are indicated by 0 or 1. Since eliteness among between populations is compared via comparison of the current population data with the ones of the best non-dominated achieved answers, the procedure of algorithms differs after the first generation. First, a combined population is formulated ($R_1 = P_1 \cup Q_1$). The number of the population R1 is 2N.

Population R1 is sorted according to non-domination. Since all members of the current and previous population are present in R1, elite ness is guaranteed. The answers of the best non-dominated category F1 are formed out of the best ones in the population. They must be strengthened more than any other answer. If F1 is fewer than N, all its members are selected for the new population Pt+1. The rest of the members of Pi+1 are chosen from the consecutive non-dominated fronts. This procedure continues until no category can exist.

3 | Findings

3.1 | NSGA-II Parameter Settings

In this part of the research, we discuss the calculated results of solving the NSGA-II meta-heuristic method. Before running the model, it is necessary to design several scenarios for the model settings using a test plan to solve it. The Taguchi approach was used to design the experiments in the NSGA-II algorithm. Thus, three diverse levels (code 1=low, code 2=medium, code 3=high) are considered for their indices. Then, the pre-determined experiments in this algorithm are implemented for all probable combinations. *Table 1* shows the recommended values for the parameters of this algorithm.

Table 1. Parameters and their levels for the NSGA-II algorithm.

Parameter	Values of Each Level		
	Level 3	Level 2	Level 1
Population Size (PS)	200	100	50
Crossover Rate (CR)	0.9	0.7	0.5
Mutation Rate (MR)	0.5	0.3	0.2
Maximum iterations (Max_iter)	200	150	100

Next, various tests were formed using Taguchi's L9 design, and the NSGA-II algorithm was implemented for all (*Table 2*). As seen, all probable modes are presented for diverse levels regarded for NSGA-II algorithm parameters. For instance, all parameters in the initial test take part in the experiment based on the minimal level. In the second one, the parameter PS possessing the minimal level value and other parameters possessing their relevant mean average level value are evident. Similarly, other probable modes are completed by the statistical permutation rule. After implementing all the tests and computing the MID values, this index estimates the optimal response level.

Table 2. Response variable values in Taguchi technique for NSGA-II.

Execution Number	Algorithm Parameters				MID Index
	PS	CR	MR	Max_Iter	
1	1	1	1	1	534.0
2	1	2	2	2	612.0
3	1	3	3	3	537.0
4	2	1	2	3	491.0
5	2	2	3	1	576.0
6	2	3	1	2	637.0
7	3	1	3	2	599.0
8	3	2	1	3	973.0
9	3	3	2	1	642.0

Now, by presenting these outputs to the MINITAB software, the S/N diagram is presented in the form of *Fig. 3*. Based on the calculated signal-to-noise ratio at all levels considered for each of the factors, the lower this value is for the desired level; the value of that level is selected for that factor. As shown in *Fig. 3*, the lowest signal-to-noise ratio in the PS factor occurs when this index is at its high level with code 3. Therefore, the value we consider for this parameter in the NSGA-II algorithm will be equal to 200. Also, the lowest signal-to-noise ratio in the CR index corresponds to the average level with code 2 of this factor. Therefore, the CR factor with a value of 0.7 will be present in the algorithm. In addition, the lowest value for the MR factor corresponds to the time when this factor is at its lowest level with code 1. Therefore, this factor will be present in the algorithm with a value of 0.2. Finally, the Max_iter factor has the lowest value relative to the noise when it is at its high level with code 3. Therefore, this factor will be present in the algorithm with a value of 200.

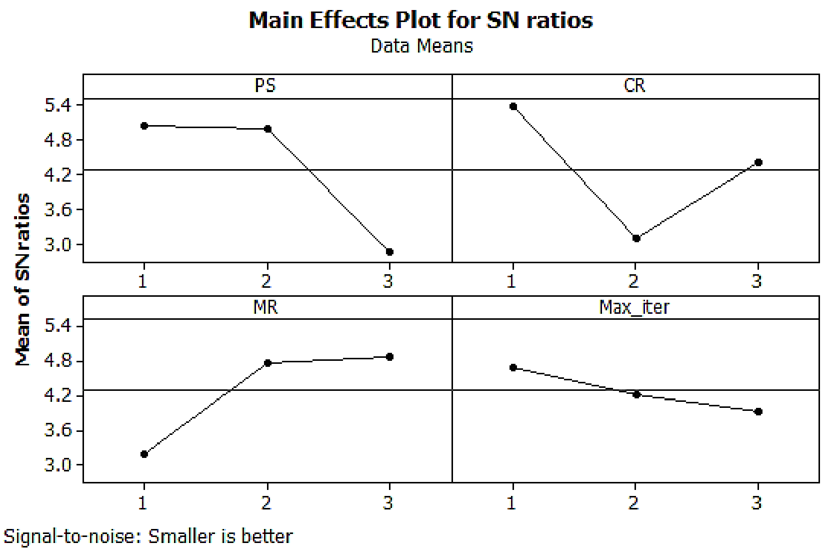

Fig. 3. Minitab output for Taguchi method in NSGA-II algorithm.

At this time, the output above-mentioned in the diagram is used to specify the optimal value of all parameters (*Table 3*), and these values of the algorithm parameters are used to implement the other examples. *Table 3* shows the best value of the factors.

Table 3. The optimal value of variables in NSGA-II.

Parameter	The Optimal Value
Population Size (PS)	200
Crossover Rate (CR)	0.7
Mutation Rate (MR)	0.2
Maximum iterations (Max_iter)	200

3.2 | Solving the Problem and Rendering Numeric Results

In this section, multi-objective problems are solved using the epsilon constraint method in the Lingo program and the NSGA-II Meta heuristic approach. Then, the optimized costs of the models are compared. First, numeric examples are designed as follows:

According to the following table, obviously, when the dimensions of numeric problems increase, the number of activities, modes, renewable and nonrenewable resources, and workdays increase. Workdays are considered the number of scheduling periods. Accordingly, the problems are solved in ten different dimensions.

Table 4. The designed experimental problems.

The Numerical Example Number	Number of Activities	Number of Modes	Number of Renewable Resources	Number of Nonrenewable Resources	Number of Workdays
1	2	1	2	1	2
2	2	2	3	2	2
3	3	2	3	2	3
4	3	2	3	3	4
5	4	3	4	3	4
6	4	3	4	4	5
7	5	3	5	5	5
8	5	4	6	6	7
9	6	5	8	9	10
10	7	5	9	9	12

Subsequently, in the following tables, the amounts are calculated via the epsilon constraint method in the Lingo program, and the NSGA-II is indicated. For numeric examples with low dimensions, the Epsilon constraint method performs better than NSGA-II. For numeric examples 1 and 2, the objective function of the total costs is less and more optimized than the ones achieved from NSGA-II. On the other hand, In the numeric examples whose dimensions are average or high (example 3 onwards), the meta-heuristic approach NSGAII has better performance in optimizing the costs compared with the epsilon constraint approach. In addition, from the numeric example 4 onwards, the exact method cannot solve the problem, and NSGA-II is more fruitful. Furthermore, a summary of answers is reported for objective functions. In the right column, the difference in optimized amounts is indicated.

Table 5. The amount of the objective function of total costs using the exact method and NSGA-II.

Example Dim.	Numerical Example	The Total Costs (the Exact Method)	The Total Cost (NSGA-II)	The amount of Difference between Optimized Numbers in the Two Methods
Small	1	9.22	12.51	%26
	2	11.6	14.49	%19
	3	27.35	25.71	%5
	4	97.12	79.16	%18
Medium	5	-	129.33	-
	6	-	198.33	-
	7	-	251.68	-
	8	-	368.12	-
Large	9	-	478.84	-
	10	-	512.3	-

In the following figure, the differences in costs are indicated in objective functions of numeric problems with various dimensions in which NSGA-II and Epsilon constraint methods are used to solve them. When the dimensions of problems increase, NSGA-II performs better than the epsilon constraint method and has the capability of solving problems with higher dimensions. It is observed that for numeric problems 1 and 2, the epsilon constraint method can reduce costs better. On the other hand, regarding the numeric examples 3 and 4, the NSGA-II algorithm is more fruitful in doing so. From example 5 onwards, the NSGA-II is more

beneficent and can be used to solve problems with higher dimensions because the epsilon constraint method is not capable of doing so.

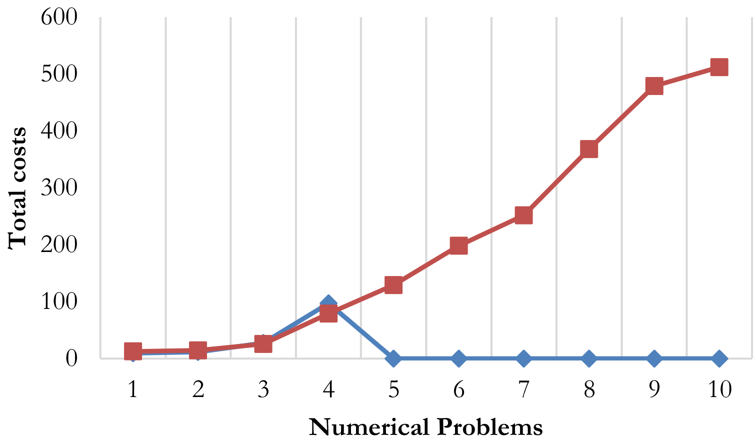

Fig. 4. The differences in problem costs using NSGA-II and the exact method after increasing the problem dimension.

Subsequently, the amounts of time delays calculated via the epsilon constraint method and the NSGA-II approach are reported. For numeric examples 1 and 2, the amount of objective function is less and more optimized than the ones achieved from the NSGA-II approach. On the other hand, In the numeric examples whose dimensions are average or high (example 3 onwards), the meta-heuristic approach NSGAII has better performance in optimizing time delays compared with the epsilon constraint method. In addition, from the numeric example 4 onwards, the exact method cannot solve the problem, and NSGA-II is more fruitful.

Table 6. The amount of the objective function of time delays using the exact method and NSGA-II.

Example Dim.	Numerical Example	Time Delays (the Exact Method)	Time Delays (NSGA-II)	The amount of Difference between Optimized Numbers in the Two Methods
Small	1	9.75	13.62	%28
	2	13.45	17.78	%24
	3	33.26	29.15	%12
	4	72.14	61.43	%14
Medium	5	-	92.01	-
	6	-	129.31	-
	7	-	141.54	-
	8	-	176.36	-
Large	9	-	211.5	-
	10	-	261.44	-

In the following figure, the differences in time delays are indicated in objective functions of numeric problems with various dimensions in which NSGA-II and Epsilon constraint methods are used to solve them. When the dimensions of problems increase, the NSGA-II approach performs better than the epsilon constraint method and has the capability of solving problems with higher dimensions. It is observed that for numeric problems 1 and 2, the epsilon constraint method can reduce time delays better. On the other hand, regarding the numeric examples 3 and 4, the NSGA-II algorithm is more fruitful in doing so. From example 5 onwards, the NSGA-II approach is more beneficent and can be used to solve problems with higher dimensions because the epsilon constraint method is not capable of doing so.

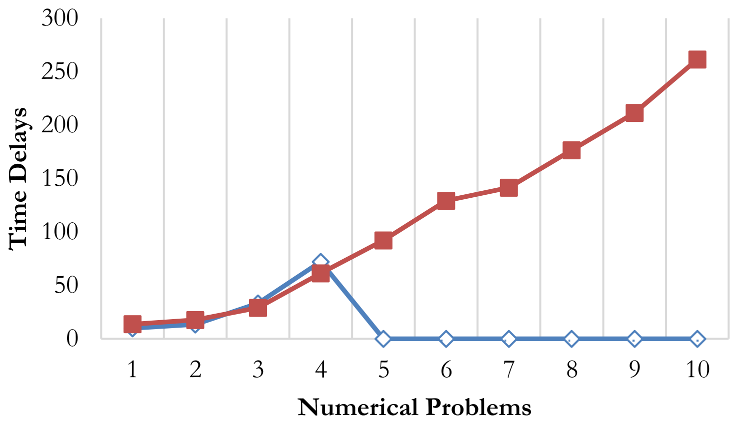

Fig. 5. The differences in time delays using NSGA-II and the exact method after increasing the problem dimension.

Subsequently, the amount of the function of reliability, which is calculated via the epsilon constraint method and the NSGA-II, is indicated. For numeric examples 1, 2, and 3, the objective function amount in the Epsilon constraint method is better and more optimized compared with the one of NSGA-II. On the other hand, in the numeric examples whose dimensions are average or high (example 4 onwards), the NSGA-II Meta heuristic method performs better in optimizing the reliability compared with the epsilon constraint method. In addition, from the numeric example 4 onwards, the exact method cannot solve the problem, and NSGA-II is more fruitful.

Table 7. The amount of the objective function of reliability using the exact method and NSGA-II.

Example Dim.	Numerical Example	Reliability (the Exact Method)	Reliability (NSGA-II)	The amount of Difference between Optimized Numbers in the Two Methods
Small	1	2.56	2.33	%8
	2	4.14	4.01	%3
	3	11.29	7.98	%29
	4	15.68	24.61	%36
Medium	5	-	26.14	-
	6	-	35.25	-
	7	-	41.67	-
	8	-	58.07	-
Large	9	-	76.14	-
	10	-	94.17	-

In the following figure, the differences in reliability are indicated in objective functions of numeric problems with various dimensions in which NSGA-II and Epsilon constraint methods are used to solve them. When the dimensions of problems increase, NSGA-II performs better than the epsilon constraint method and has the capability of solving problems with higher dimensions. It is observed that for numeric problems 1, 2, and 3, the epsilon constraint method can increase reliability better. On the other hand, regarding the numeric example 4, the NSGA-II algorithm is more fruitful in maximizing reliability. From example 5 onwards, the NSGA-II is more beneficent and can be used to solve problems with higher dimensions because the epsilon constraint method is not capable of doing so.

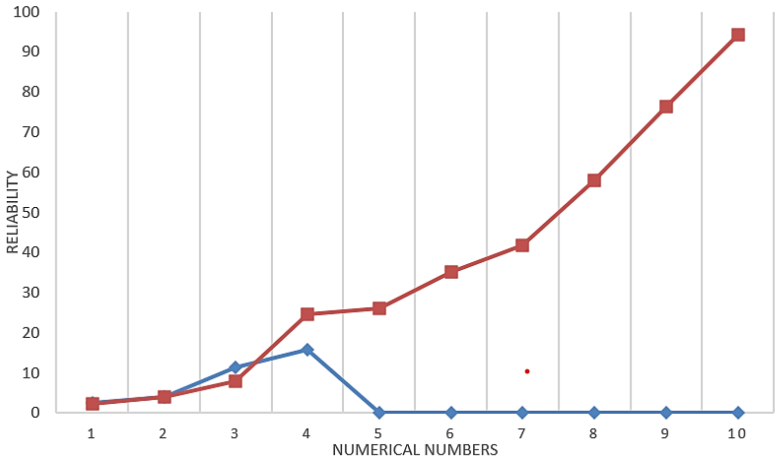

Fig. 6. The differences in reliability using NSGA-II and The exact method after increasing the problem dimension.

In the following section, the project scheduling method is indicated. *Fig. 7* is about the numerical problem 5, which entails 4 activities in four work hours. Obviously, some activities lasted 2 work days. Activity 2 lasted one work day, and the ones 2 and 3 lasted two work days. This scheduling is done regarding renewable and nonrenewable resources.

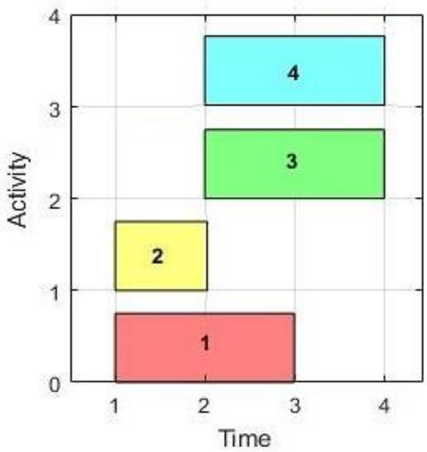

Fig. 7. The scheduling of activities-four activities in the NSGA-II method.

After presenting the results achieved via the Lingo and NSGA-II approach, the numeric sensitivity is analyzed in order to find out the validation and test the models. Our method is that by changing the parameter of the resource number of the Kth renewable resource, the model and its changes are analyzed regarding objective functions of costs and time delays in the meta-heuristic approach NSGA-II.

3.3 | Sensitivity Analysis

Figs. 8-10 indicate that increasing the number of renewable resources results in the total system becoming more costly. When the numbers increase from 9 to 13, the increase in costs is relatively constant. That is not the case when they increase from 14 to 15.

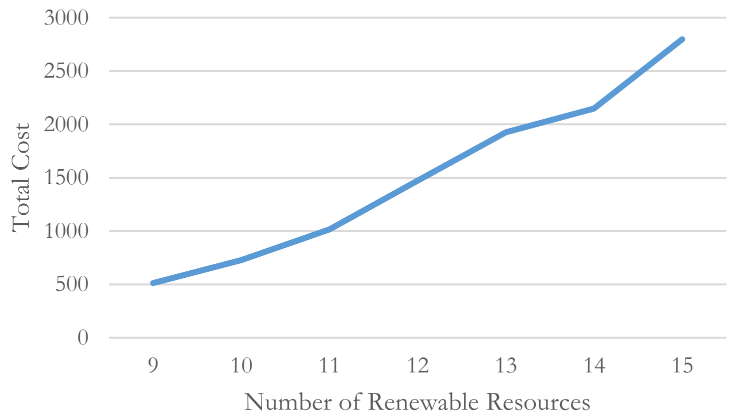

Fig. 8. The amount of change in the objective function of costs when the number of renewable resources increases.

In the subsequent figure, when the number of renewable resources increases, there is no change in time delays. Consequently, this objective function does not depend on the number of renewable resources.

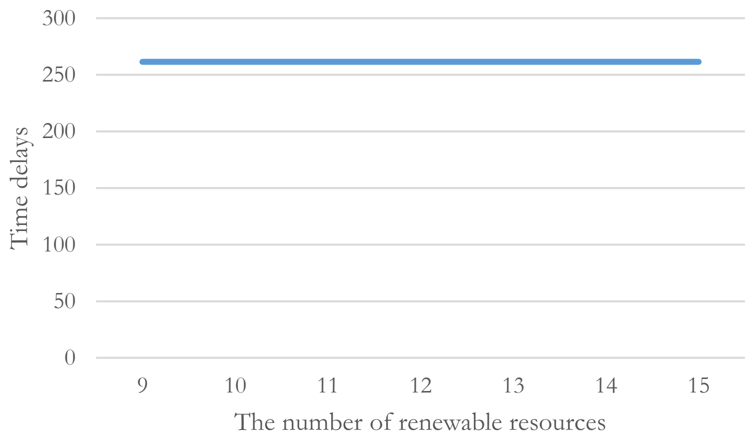

Fig. 9. The amount of change in the objective function of time delays when the number of renewable resources increases.

Subsequently, it is indicated how the reliability objective function changes according to the increase in the number of renewable resources. We can see that increasing the number of renewable resources results in raising reliability in the form of the exponential function. The amount of this raise is higher than that of one of the cost objective functions. Regarding 13, 14, and 15 resources, reliabilities raise significantly and are more than increase in the cost one. It is revealed that raising the number of renewable resources results in a decrease in the optimization of the reliability objective function.

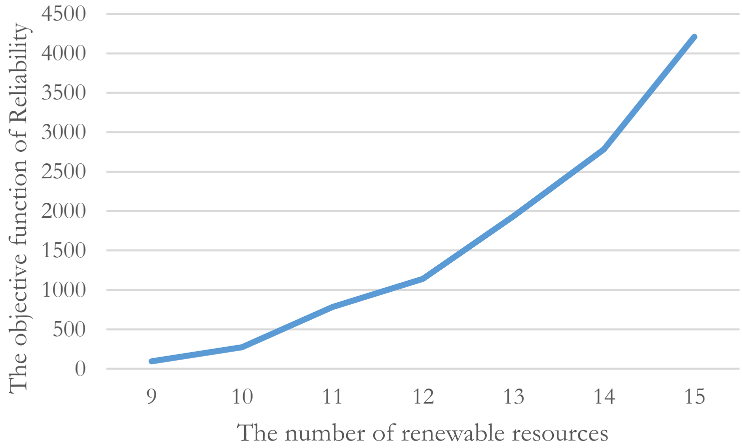

Fig. 10. The amount of change in the objective function of reliability when the number of renewable resources increases.

4 | Discussion

In this paper, a solution framework based on mathematical programming and meta-heuristic algorithms for the problem of RCPSP is presented. For this purpose, mathematical modeling has been developed for the RCPSP problem, which has been solved using the epsilon method deterministically on small numerical samples and then using the NSGAII meta-heuristic algorithm for problems with larger dimensions. In order to develop the RCPSP problem in this research, we have added the reliability function to functions such as cost and time delay that have been considered in the past. Because we showed that the reliability function can guarantee the availability of renewable resources, since the optimization of RCPSPs has its complexities, in this research, a meta-heuristic GA is used to solve the mathematical model. The final optimized answers will be compared with the answers using the exact method. In the next section, the problem and its constraints, variables, and parameters are modeled. After that, numerical examples will be presented and solved using the Lingo and NSGA-II meta-heuristic algorithm, which is very useful for solving multi-objective optimization problems.

The final results of these two methods have been compared. Therefore, this paper aims to fill the research gap through two major activities. First, an optimization model has been presented to solve the RCPSP problem using mathematical modeling and the NSGAII meta-heuristic algorithm. Secondly, the maximum reliability objective function is considered as the objective function in the RCPSP problem in order to maximize the reliability of the availability of renewable resources.

5 | Conclusion

In this study, the RCPSP was investigated, and presuppositions and previous models regarding scheduling were considered along with a third objective function in the math model, which is reliability. Considering how much renewable resources are possibly available, this study investigated the scheduling of projects from the perspective of probability. In order to do so, a complex non-linear math programming model was designed to transform into a complex linear one because of the features of exponential functions. This method was rarely used to make models linear in the literature review of these studies. The multi-objective optimization was used in this study since the designed math model includes three objective functions: costs, time delays, and reliability.

In the case of problems with low dimensions, the exact epsilon constraint method was applied. In one of the problems with averaged and high dimensions, the NSGA-II, a multi-objective Meta heuristic algorithm, was put into use. In the end, the results were compared in order to analyze the performance of both methods in

solving problems with various dimensions. After solving the problem, we concluded that in the case of lower dimension problems, the exact epsilon constraint method renders better results, while in the cases of average and high dimension ones, this method is not applicable, and the NSGA-II algorithm is more fruitful.

Furthermore, from the numeric examples 5 to 10, the epsilon constraint approach cannot be used. On the other hand, in order to validate the designed model, the numeric sensitivity of the number of renewable resources parameters and the model behaviors and changes of objective functions of cost, time delays, and reliability were analyzed via the NSGA-II approach. In the end, a rise in the parameter of the number of renewable resources increased the objective function of costs and reliability. The difference is that the rise in reliability was much higher compared with costs. The most important limitation of this research is facing problems with large dimensions, which the mathematical model is not able to solve if the dimension of the problem increases and becomes more complicated.

In this case, the use of meta-heuristic algorithms is considered in the proposed framework to overcome such a situation. As a suggestion to expand the current study on the RCPSP criterion, uncertain data can be used for some parameters in the problems in order to be closer to reality. Also, to deal with uncertainty, robust optimization, fuzzy programming, and probabilistic programming can be used to consider different dimensions of an RCPSP problem. By using these methods, the values of the objective and optimization function can be compared in certain and uncertain ways. In addition, meta-heuristic algorithms such as multi-objective Gray Wolf Optimization (GWO) or Imperial Competitive Algorithm (ICA) can be used in RCPSP, and their performance can be compared. To see if there is a more efficient algorithm than the GA in solving this problem.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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